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Fares and Network 'Feed': Estimating Economies of Traffic Density in Airline Hub-and-Spoke Systems

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November 1991

Abstract

This paper explores the determinants of airfares paid by hub-and-spoke passengers, focusing in particular on the effects of traffic densities on the network spokes along which they travel. Using both structural and reduced-form approaches, we find that high spoke densities lead to low fares, confirming the existence of the economies of traffic density first identified by Caves, Christensen and Tretheway (1984) while showing that the resulting cost savings are passed on in part to consumers. We also report estimates of the airlines' marginal cost and demand functions using a structural approach. Our results reveal economies of density stronger than those found by Caves et al. Finally, we use the structural estimates to simulate the welfare effects of airline mergers.

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1. Introduction

Airline deregulation has led to fundamental changes in both firm organization and industry structure. At the firm level, the elimination of restrictions on entry and exit dramatically altered the way airlines conduct their operations. Granted the freedom to fly wherever they wish, the carriers responded by transforming their route structures into hub-and-spoke networks, where passengers change planes at a hub airport on the way to their eventual destinations.[1] By feeding all passengers through a hub, such a network generates high traffic densities on its spoke routes. This allows the airline to exploit economies of traffic density, under which cost per passenger on a non-stop route decreases as traffic on the route rises.[2] Network "feed" (the flow of passengers through the hub) thus generates efficiency gains, reducing the cost of providing airline service.

In addition to stimulating the growth of hub-and-spoke networks,

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[1]For discussion of the impact of the new regulatory environment on airline operations, see Bailey and Williams (1988), Bailey, Graham and Kaplan (1985), Levine (1988), Moore (1986), and Morrison and Winston (1986). A measure of the increase in "hubbing" is provided by McShan and Windle (1990), who show that the total enplanements of each carrier became increasingly concentrated at selected airports over the 1980's (Bailey *et al*. (1985) provide similar data for departures).

[2]Economies of density arise because high density allows the airline to use larger, more efficient aircraft and to operate these aircraft more intensively (at higher load factors). See Bailey *et al*. (1985), especially Tables 3.4 and 3.5. In addition, higher densities allow more intensive use of fixed ground facilities as well as more effective aircraft utilization (more flight hours per day).

deregulation has also led to structural changes in the industry. Most importantly, the industry has become more concentrated at the national level, raising concerns about the exercise of market power by the large airlines.[3] In addition, concentration has increased locally at certain hub airports, which are now dominated by a single carrier. This development has raised concerns about the exercise of market power over local traffic at the dominated hubs.[4] In contrast, competitive conditions in the <u>average</u> city-pair market have improved over the period of deregulation. As shown by Morrison and Winston (1991), the number of competing airlines per market has increased over the period despite the growing concentration of the industry.[5]

These changes in industry structure are in part a consequence of the changing organization of firms, as reflected in the growth of hub-and-spoke networks. First, given that such networks allow carriers to exploit economies of density, firms with large, dense networks enjoy low costs per passenger, which yields a competitive advantage. Therefore, the development of hub-and-spoke networks may help explain the demise of smaller carriers and the

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[3]Morrison and Winston (1991) show how the number of effective competitors in the industry, which equals the inverse of the Herfindahl index, has changed since deregulation. This number was around 9.5 in 1978, rose to over 11.5 by early 1985, and then fell to around 8.0 by 1989 following a number of mergers and bankruptcies. Other changes in industry structure are also thought to inhibit competition, namely the use of computerized reservation systems and the existence of marketing arrangements with travel agents.

[4]By 1988, single carriers controlled 60% or more of the traffic at the following major airports: Atlanta, Charlotte, Cincinnati, Detroit, Minneapolis, Pittsburgh, Raleigh-Durham, St. Louis, and Salt Lake City. Borenstein (1989) provides empirical evidence regarding the effect of hub dominance on fares.

[5]In 1978, the average number of effective competitors per market (the average across markets of the inverse of the market Herfindahl index) was slightly above 1.5. This number had grown to a value slightly below 1.9 by the end of 1989 (see Morrison and Winston (1991).

difficulty of entry by new firms (and thus the increase in industry concentration). Second, since the operation of a hub-and-spoke network requires heavy use of a hub airport, such an airport tends to become dominated by the network airline. Thus, acquisition of local market power in the hub city is often concomitant to the development of a network. Finally, the increase in competition in the average market may be due to an additional effect of hub-and-spoke operations: the lowering of entry costs into individual city-pair markets. Airlines can now enter a host of new markets by simply adding a new city to the network (service can then be provided between that endpoint and any other city served from the hub).

Given the efficiency gains from network operations, and the associated growth in competitors per market, the hub-and-spoke system appears to offer substantial benefits that may offset the system's unfavorable effects on industry concentration and on the welfare of hub-city passengers. However, because hub-and-spoke networks have received little attention by researchers, the magnitude of such benefits is unknown. The purpose of the present paper is to explore one aspect of hub-and-spoke benefits by attempting to quantify the efficiency gains from network operations. The paper tests for the presence of economies of traffic density and attempts to measure the strength of the density effect.

Some progress toward these goals has already been achieved by Caves, Christensen and Tretheway (1984), who estimate the extent of economies of density by analyzing the relationship between airline total costs, route structure, and total passenger traffic. They find that, holding the airline's route structure (the number of points served) constant, total cost increases only 80% as rapidly as total traffic, indicating significant economies of density. While this is an important finding, there has been no parallel study of the connection between the fares that airlines actually charge and the traffic densities on their routes. We explore the density effect using this alternative method. Relying on detailed Department of Transportation data, we study airline fares for city-pair markets in which travel requires a connection at a hub airport. We find that the fare paid by a connecting passenger is low when the traffic densities on the two network spokes along which he travels are high. This effect holds constant other variables (such as competition and tourism potential) that affect fares in the city-pair market. Our finding of an inverse relation between fares and spoke traffic confirms the existence of the economies of density identified by Caves et al. (1984) and shows that the gains are in part passed on to passengers. This is an important finding because it shows that hub-and-spoke operations have indeed benefitted consumers.

Although these reduced-form regression results show that consumers pay relatively low fares when travelling on dense spokes, they do not reveal the extent of the cost savings from higher density (nor what fraction of these savings are passed on to consumers). To directly estimate the strength of economies of density, we develop a structural model of competition among hub-and-spoke airlines. Estimation of such a model requires assumptions about the nature of the oligopoly game played by the airlines as well as the functional forms of demand and marginal cost. Estimated economies of density in the structural model turn out to be stronger than those reported by Caves et al. (1984). The procedure also generates plausible demand elasticities.

As a final exercise, we use the above structural estimates to investigate an important public policy question: the welfare effect of hypothetical airline mergers. There has been considerable concern about the welfare effects of mergers which, like those of TWA-Ozark and Northwest-Republic, lead to the creation of a monopoly hub airport. As explained above, the post-merger airline's monopoly power over hub-originating and hub-terminating passengers is expected to raise fares substantially for those passengers. We have argued elsewhere, however, that connecting passengers, who are not subject to monopoly power, may actually benefit from the merger as a result of the creation of a larger, more densely-travelled network (see below). Using the structural estimates, we address these issues by simulating the effects on fares and overall welfare of a TWA-Ozark-type merger. The forces at work are familiar from standard oligopoly models: a merger under increasing returns leads to lower costs while at the same time reducing competition. The welfare outcome depends on the relative strength of these two effects. Our simulations suggest that the balance tips in one direction in the case of a TWA-Ozark-type merger while showing how fare impacts vary between connecting passengers and those travelling to or from the hub (the simulations also show the merger's spillover effects on competing networks).

The present paper builds on the approach of an earlier paper (Brueckner, Dyer and Spiller (1990); hereafter BDS), which offered indirect evidence on the connection between economies of density and fares. Rather than relating fares directly to spoke traffic levels, BDS explored the relation between fares and network characteristics, proceeding on the assumption that traffic within a network is ultimately a function of its characteristics. For example, BDS hypothesized that spoke traffic in a network is an increasing function of the <u>size</u> of the network, as measured by the number of city pairs that it connects (a large network offers many destinations, and thus generates high traffic levels on each of its spokes). This effect, together with economies of density, implies that fares for connecting passengers should be <u>inversely related</u> to the size of the network in which a trip occurs. BDS's regressions showed that network characteristics are indeed important determinants of fares. In this paper, we perform a more stringent test of BDS's basic hypothesis by studying the link between fares, marginal costs, and actual spoke traffic levels.

Our paper follows BDS in extending a recent literature that studies the determination of fares in airline city-pair markets. This literature, which contains notable contributions by Bailey, Graham and Kaplan (1985), Berry (1990), Borenstein (1989), Call and Keeler (1985), Graham, Kaplan and Sibley (1983), Hurdle et al. (1989), and Morrison and Winston (1989, 1990), explores the connection between airfares and market-specific variables. These include measures of demand (city populations and incomes), cost (flight distance and load factors), and competition (number of competitors, market share). BDS criticized this literature for its failure to include network characteristics in its fare regressions. The present study, which goes beyond the reduced-form approach of BDS, makes this point even more clearly: Given that marginal costs and fares in a city-pair market are shown to depend critically on traffic levels along the spokes connecting the market cities, and given that these spokes carry traffic in a multitude of other city-pair markets, fares in the given market depend on the operation of the entire network. Therefore, network considerations must be included not only in any fare regression but in any structural analysis of the airline industry.[6]

The plan of the paper is as follows. Section 2 presents an overview of our methodology, while section 3 presents the results of the reduced-form fare regression. Section 4 presents the structural estimates, and Section 5 carries out the merger simulations. Section 6 offers conclusions.

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[6]Using an approach similar to ours, Hurdle et al. (1989) include a measure of traffic density on the route segment serving a city-pair market (which includes passengers travelling beyond the endpoints of the market) in a regression explaining fares. However, under their specification, this variable (which plays a minor role in the study) has no significant impact on fares.

2. Overview of Methodology

Data for the study are drawn from Databank 1A (DB1A) of the Department of Transportation's Origin and Destination Survey. This databank shows fare and route information for a quarterly 10% sample of all airline tickets sold in the U.S. Each record of the databank contains an airline itinerary (a route flown on a given carrier, with the direction of travel indicated), a dollar fare, the distance of the trip, and the number of passengers flown on the itinerary at the given fare during the quarter. The sample period is the fourth quarter of 1985.

As explained above, our task is to see whether economies of density are revealed in the DB1A fare data. We explore the density effect by focusing on 4-segment city-pair markets, where passengers change planes at a hub airport during their trip (the round trip thus involves 4 flight segments). 2-segment (i.e., nonstop) markets are not considered on the grounds that they are less likely to reveal a density effect. This is true because the endpoints of many 2-segment markets are hub airports dominated by a single carrier, whose market power raises fares above costs, obscuring any density effect (see Borenstein (1989)). In addition, most 2-segment travel occurs on dense route segments between large cities, where economies of density may be exhausted. By contrast, 4-segment passengers are likely to travel on at least one low-density network spoke (serving a small or medium-size endpoint), where economies of density are unexhausted (and thus observable). To illustrate the extent of 4-segment travel through hub airports, the appendix shows the number of 4-segment city-pair markets served by the major hub-and-spoke networks in the sample, along with other relevant network characteristics (these are computed from the DB1A data).[7]

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[7]In compiling the data set, attention is restricted 4-segment single-carrier round trips where the connecting (hub) airport is the same in both directions. Records whose itineraries show travel outside the U.S. are

Fares in a 4-segment market will depend, in part, on the carrier's marginal cost of serving an additional passenger in the market. Marginal cost in turn depends on flight distance and on carrier characteristics such as labor cost. With economies of traffic density, another factor exerts an important influence on marginal cost: total traffic levels on the two network spokes used by passengers in the market.

To understand the role of spoke traffic, consider the simple network shown in Figure 1, which connects three endpoints out of hub A and thus serves three 4-segment markets: ij, ik, and jk. Let $c(Q)$ denote the cost of operating a single spoke of the network as a function of traffic on that spoke. The marginal cost of serving a passenger in market ij is then equal to $c'(Q_i) + c'(Q_j)$, where Q_i and Q_j are total traffic levels on spokes i and j. Since economies of density imply $c'' < 0$, marginal cost is decreasing in Q_i and Q_j. Moreover, if the marginal cost function is linear in Q, then $c'(Q_i) + c'(Q_j)$ is simply a function of $Q_i + Q_j$, total traffic on the spokes connecting the market cities.[8] Thus, in the linear case, a passenger's marginal cost in market ij depends on $Q_i + Q_j$, flight distance, and carrier-specific fixed effects (which

excluded, as are itineraries where one or both endpoints did not appear on a chosen list of 267 cities. In addition, in computing the network characteristics shown in the appendix, we restrict attention to DB1A records with passenger levels of 2 or greater (corresponding to quarterly traffic of 20). There are 23,428 4-segment itineraries satisfying these requirements, involving travel in 8179 distinct nondirectional city-pair markets (the difference arises because itineraries are directional and because multiple carriers and multiple same-carrier routes serve a given market). As pointed out by BDS, the volume of 4-segment traffic in the sample period was about one-half the volume of 2-segment traffic. It should be noted that the fare regressions reported below are based on subset of the data used to generate network characteristics (only those DB1A records with 4 or more passengers are used in order to exclude extremely thin markets).

[8] It is important to note that since passengers in other markets travel along spokes i and j, $Q_i + Q_j$ (and thus marginal cost in market ij) depends on the operation of the entire network (along with ij traffic, Q_i includes traffic in market ik and traffic between i and the hub, and similarly for Q_j).

represent labor costs and other determinants of operating costs). Note that since a decline in marginal cost tends to reduce fares, fares should be inversely related to $Q_i + Q_j$ with economies of density. Summary data on spoke traffic is provided in the appendix, which shows average spoke traffic levels for the major hub-and-spoke networks.[9]

Two additional forces help determine fares in a city-pair market: demand and the level of competition. Competition is measured by simply counting the number of market competitors. Demand is assumed to depend on the size of the market (a function of the populations of the endpoint cities), on income in the market, and on the market's tourism potential. These factors, along with the variables underlying marginal cost, determine equilibrium fares in the market. Fares thus depend on spoke traffic; distance; carrier fixed-effects; market size, income, and tourism potential; the level of competition.

One approach to testing for economies of density is simply to regress fares on this list of variables, estimating a reduced-form equation.[10] The coefficient of spoke traffic in this regression should be negative in the presence of economies of density. While this approach shows the equilibrium response of fares to changes in the market variables, it does not reveal the

[9]Spoke traffic data comes from the DOT's Service Segment Databank DB27R, which shows a carrier's total monthly traffic on each nonstop route segment that it serves (traffic is aggregated across individual flights). These traffic levels, as well as those used in the regressions, are found by summing traffic in both directions on the spoke and dividing by two (this is done for the 4th quarter of 1985).

[10]While most of the explanatory variables in this regression are unambiguously exogenous, the status of the spoke traffic and competition variables requires discussion. Below, we argue that since each city-pair market contributes negligibly to total spoke traffic, this variable is properly viewed as exogenous. The same conclusion need not apply to the level of competition, which may be determined jointly with fares. However, we explain below that a proper simultaneity correction is difficult to carry out. Our regression thus contains a potentially endogenous variable, which means that the equation is probably best view as a "quasi reduced-form."

underlying structure of marginal cost and demand. In particular, the approach does not reveal the strength of economies of density (the coefficient of spoke traffic in the marginal cost function). To estimate the structural parameters, additional assumptions must be made regarding functional forms and the nature of competitive interactions. The resulting structural model can then be estimated, recovering the parameters of interest.

Both these approaches are carried out below. In Section 3, we report the results of estimating a reduced-form equation. For comparability with our earlier work, the specification of this equation is identical to that in BDS, except that spoke traffic is used in place of network characterisitics. The regression results confirm the presence of economies of density, justifying a more ambitious attempt to estimate structural parameters. The structural model, which is developed in Section 4, assumes linear demand and marginal cost as well as Cournot behavior on the part of the airlines. Estimation makes use of the model's two reduced-form equations (one for the fare, one for traffic in the market). These equations are estimated jointly by maximum likelihood taking cross-equation restrictions into account. In the structural model, the carrier-specific fare data are aggregated up to the market level (an average market fare is used). By contrast, each observation under the reduced-form approach corresponds to a fare charged by a particular carrier.

3. Reduced-Form Estimation

We begin by identifying the specific variables used in the reduced-form regression. Many of these variables appear later in the structural model.

a. Explanatory variables

First, as explained above, the spoke traffic variable is equal to the sum of the traffic levels on the two spokes connecting the endpoints of the city-pair market to the carrier's hub (traffic is for the fourth quarter of 1985).

This variable, denoted SPKPASS, is thus equal to SPKPASSO + SPKPASSD, where SPKPASSO is traffic on the spoke connecting the market's origin city to the hub and SPKPASSD is traffic on the spoke connecting the market's destination city to the hub (variable definitions are found in Table 1). Recall that when the spoke marginal cost function is linear, the marginal cost of serving a passenger in the market depends on the sum of SPKPASSO and SPKPASSD.

Variables used along with spoke traffic to capture carrier costs are DIST, one-way flight distance on the route; a set of carrier dummy variables (American is the default carrier); and dummy variables that assume the value 1 if one endpoint of the market is a particular slot-controlled airport (slot control raises the cost of providing airline service at the airport). These dummies are denoted ORD (Chicago-O'Hare), LGA (La Guardia), DCA (Washington-National), and JFK (John F. Kennedy).

Three variables measure the demand for travel in a city-pair market. The first is MKTPP (market population potential) and is equal to $(POP_i POP_j)^{1/2}$ for market ij, where POP is city population measured in 10,000s.[11] This variable is a measure of the size of the market. The second demand variable is INCORIG, which equals per capita income for the origin city. Use of origin income, rather than a composite measure of income at both market endpoints, reflects our expectation that although published fares are nondirectional, observed fares will depend on the direction of travel in a market. High income at the origin city is likely to result in reduced sensitivity to the cost of travel by origin residents and thus greater willingness to purchase less restrictive (and thus more expensive) directional tickets. Another directional demand variable is TEMPDIF, equal to the destination's mean January temperature minus the origin's mean January temperature. A high value of TEMPDIF, which indicates

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[11] This variable is also used by Graham, Kaplan and Sibley (1984) and Call and Keeler (1985).

that origin residents are likely to engage in vacation travel in the market, is expected to lead to lower observed fares as these passengers select the most restrictive (and hence cheapest) tickets.[12]

Competition is measured by computing the total number of carriers competing with the observed carrier in the market, denoted MKTCOM (competition could be via 4-segment or nonstop service).[13] While MKTCOM can be used directly, we let the effect of extra competition depend on the initial number of competitors by constructing the variables MKTCOM1, MKTCOM23, and MKTCOM4+ (this follows BDS). MKTCOM1's coefficient gives the effect on fares of increasing MKTCOM from 0 to 1; MKTCOM23's coefficient gives the effect of increasing MKTCOM from 1 to 2 or from 2 to 3; MKTCOM4+'s coefficient gives the effect of increasing MKTCOM from 3 to 4 and beyond.[14] These coefficients are

[12]As argued by BDS, observed fares may also differ by direction as a result of yield manangement by the carriers. Residents of a high-income origin city may find few cheap seats on the most convenient flights (e.g., morning departures) to some low-income destination. Cheap seats may be abundant, however, on convenient departures from the low-income city to the high-income destination. Through yield management, the carrier can therefore price discriminate within a given market on the basis of city income despite the fact that published fares are nondirectional.

[13]A carrier was counted as a competitor if it was observed carrying 2 or more passengers in either direction in the market. Also, if the same competing carrier served the market via two different routes (i.e., nonstop and connecting), it was counted as two competitors (by offering passengers more choice, multiple routings yield more effective competition than a single route). The potential endogeneity of MKTCOM is discussed below.

[14]These variables, which are adapted from Morrison and Winston (1989), are defined as follows:

$$\text{MKTCOM1} = \begin{cases} \text{MKTCOM if MKTCOM} = 0,1 \\ 1 \text{ otherwise} \end{cases}$$

expected to be negative and declining in absolute value, indicating diminishing returns to competition. To measure potential competition in the market, we use the variable MKTPCOM, which is equal to the number of carriers that serve both endpoints of the market but do not provide service in the market itself.[15]

b. Results

We ran fare regressions on the subset of 4-segment DB1A records showing 4 or more passengers during the quarter (for a predicted total of 40).[16] Results were computed for two different samples drawn from this data set. The first sample treats multiple fares charged by a carrier on a given route as distinct observations, using all records in the data set (this yields 13,308 observations). An alternative approach is to aggregate multiple fares into a single value for each carrier on a route. This is done by taking a simple average of a carrier's multiple fares, a procedure that yields 7732 observations (this shows that, on average, there are slightly fewer than 2 observed fares per carrier on each route).[17] These two samples are referred to

$$\text{MKTCOM23} = \begin{cases} 0 \text{ if MKTCOM} = 0,1 \\ \text{MKTCOM-1 if MKTCOM} = 2,3 \\ 2 \text{ otherwise} \end{cases}$$

$$\text{MKTCOM4+} = \begin{cases} 0 \text{ if MKTCOM} = 0,1,2,3 \\ \text{MKTCOM-3 otherwise} \end{cases}$$

[15]This approach again follows Morrison and Winston (1989).

[16]Recall that the data comes from a 10% sample of tickets. Following the approach of BDS, records whose network showed a NTWCITP4 value of less than 10 were dropped (see the appendix), as were records where the origin or destination was a hub for the carrier (one spoke of such an itinerary connects two of the carrier's hubs). Records with a fare of less than $10 were also dropped.

[17]Computing the passenger-weighted mean fare, as done by BDS, leads to nearly-

below as the "individual-fare" and "mean-fare" samples. Finally, as in BDS, the dependent variable for the regression is the log of the round-trip fare (as explained further below, results are not sensitive to the functional form of the equation).

Table 2 reports the estimated coefficients from the reduced-form fare regressions (the individual-fare results are in the first column and the mean-fare results are in the second column). Estimated coefficients of the carrier and slot-control dummies from the mean-fare regression are reported in Table 3. The coefficient of SPKPASS is significantly negative in the equations of Table 2, showing that fares in a city-pair market are low when traffic on the spokes connecting the cities is high. This finding confirms the existence of economies of traffic density and shows that the resulting cost savings are partly passed on to consumers in the form of lower fares. The result, moreover, has public-policy significance because it identifies a potential source of the benefits of deregulation (exploitation of economies of density via hub-and-spoke networks).

For a concrete illustration of our result, consider the city-pair market Champaign, Illinois-Cleveland (CMI-CLE), served by United through its Chicago-O'Hare (ORD) hub. Our result says that United's fares in the CMI-CLE market will be lower the higher are the traffic levels on the CMI-ORD and CLE-ORD spokes of its network. The spokes in question, of course, carry United traffic in a multitude of other city-pair markets (the CMI-ORD spoke carries traffic in all markets with CMI as an endpoint, while the CLE-ORD spoke carries traffic in all markets with CLE as an endpoint). United's CMI-CLE fares thus depend on traffic levels in many other markets and, therefore, on the operation of its entire network.

Turning to the other estimated coefficients, the low t-statistics for

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identical results.

MKTPP and INCORIG suggest that market size and income have no impact on fares when spoke traffic and competition are held constant.[18] A tourism effect, however, does emerge strongly in the results, with TEMPDIF's significantly-negative coefficients indicating that observed fares are lower in vacation markets as passengers select the most restrictive tickets. Finally, the results indicate that fares are increasing in distance flown.

The estimates also show diminishing returns to competition, with the coefficients of MKTCOM1, MKTCOM23, and MKTCOM4+ significantly negative and declining in absolute value in each equation. The significantly negative coefficients of MKTPCOM also show that potential competition reduces fares. It is worth noting that correlation between MKTPCOM and SPKPASS reduces both size and significance of SPKPASS's coefficient. The third column of Table 2 shows that when MKTPCOM is deleted from the mean-fare equation, SPKPASS's coefficient increases by 60% in absolute value.[19,20]

Recalling the dependent variable is the log of the fare, the impacts in percentage terms of changes in the right hand variables follow immediately. Using coefficients from column 2 of Table 2, a one-standard-deviation increase

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[18]While the absence of an income effect contradicts expectations, INCORIG does have a significantly positive coefficient when the regression is run on the subsample of observations where the fare class is coach discount (YD) for all segments of the trip (see footnote 24). MKTPP's coefficient is significantly negative in that regression.

[19]Note that the coefficient of MKTPP is significantly negative in the third equation. Correlation between MKTPCOM and MKTPP also reduces the explanatory power of the latter variable.

[20]It should be noted that there are a number of inexplicably "thin" spokes in the data. For example, in the mean-fare sample, there are 125 observations where either SPKPASSO or SPKPASSD is less than 500, a number that corresponds to spoke traffic of around 5 passengers per day. However, deleting these observations from the sample has little effect on the results. The SPKPASS coefficient is then -0.000000345, a value almost identical to the estimate in the second column of Table 2.

in SPKPASS above its mean value of 65,345 (an increase of 32,924) leads to a reduction in the city-pair market's mean fare of 1.2%.[21] Using the second mean-fare equation (column 3), the same increase in SPKPASS leads to a larger 1.9% fare decrease. While these effects seem modest, results based on a structural model yield larger fare impacts, as will be seen below. From column 2, a 10% increase in distance leads to a 2.6% fare increase, while a one-standard-deviation increase in TEMPDIF (equal to 21.3) above its mean value of 3.5 leads to a 2.3% fare reduction. If the number of competitors in the market (MKTCOM) increases from zero to one, fares fall by 7.1%. If MKTCOM increases from one to two or from two to three, fares fall by a further 5.9%; further unit increases in MKTCOM reduce fares by 0.4%. If the number of potential competitors (MKTPCOM) increases by one, fares fall by 1.9%.[22]

The estimated coefficients of the slot-control and airline dummies from the mean-fare regression are reported in Table 3. Only the ORD and DCA dummy coefficients are significant with the anticipated positive sign. The carrier dummy coefficients show substantial fare differences across carriers (recall that American is the default carrier). Especially noteworthy are the 24%

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[21]These statistics are from the mean-fare sample. Note that traffic on a spoke used by a passenger in an average market is half of the above figure, or about 32,500. This number is much higher than the average spoke traffic from Table A-1 in the appendix, which is computed by averaging across network spokes rather than across markets. This discrepancy attests to the fact that any sampling procedure will pick up disproportionate numbers of passengers from "thick" spokes.

[22]Further mean-fare sample information is as follows. The mean value of MKTCOM is 3.2, and the relative frequencies of observations with MKTCOM equal to 0, 1, 2, 3, 4, 5, and 6 or more are 21.9%, 17.8%, 15.2%, 10.6%, 8.8%, 6.3%, and 19.3% respectively. The mean value of MKTPCOM is 2.4, and the relative frequencies of observations with MKTPCOM equal to 0, 1, 2, 3, 4, and 5 or more are 13.3%, 21.3%, 23.2%, 19.4%, 12.1%, and 11.7% respectively. The mean values of MKTPP and INCORIG are 160.8 and $10,078 respectively. Finally, the mean fare is $294 and the average number of passengers per observation is 12, corresponding to quarterly traffic of 120.

premium charged by Delta and the 22% and 52% discounts offered by America West and Air Cal respectively.

The above regressions have been viewed as reduced-form equations, in which all right hand variables are exogenous. This assumption requires justification in the cases of SPKPASS and MKTCOM. Given that SPKPASS is the sum of (endogenous) traffic levels in all city-pair markets that use the given spokes, it might appear that this variable should be treated as endogenous. However, becauses SPKPASS is largely determined by traffic levels in other markets, it can be treated as exogenous relative to the fare in any given market (this claim will be explained more fully in the next section). As for MKTCOM, it can be argued that the level of competition in a city-pair market is jointly determined along with the fares charged in the market. However, proper handling of this simultaneity requires a structural model of entry within airline networks, which is beyond the scope of this paper.[23] While the simultaneity issue can be addressed in the usual way via two-stage least squares (see BDS), we chose not to pursue this approach in the present paper, relying instead on OLS methods.

As explained above, BDS estimate a fare equation where network characteristics appear as proxies for spoke traffic. Aside from this difference, the specification of BDS's equation is identical to that in Table 2.[24] BDS hypothesize, for example, that spoke traffic is an increasing function

[23]For analysis of entry, see Berry (1989) and Reiss and Spiller (1989). The entry issue, however, may be different in a network context from the one analyzed by these authors. The reason is that entry in a particular city-pair market by a network airline entails simultaneous entry in many other markets (providing new service in a market means adding a spoke to the carrier's network, which in turn allows service to a host of additional markets). Since the presence of competition in a city-pair market will thus depend partly on network factors, a simple model positing joint determination of fares and competition in each individual market will be inaccurate.

of network size, and thus anticipate a negative size coefficient in the fare equation. BDS's results confirm this expectation and show that other density-related network characteristics have anticipated impacts on fares. Although BDS plausibly argue that their results are due to a density effect, this claim is not actually tested because no direct evidence on the link between network characteristics and spoke traffic is provided. Using the spoke traffic data, this link in BDS's argument can now be verified. This exercise is carried out in the appendix, which reports the results of a regression of SPKPASS on network characteristics. This regression shows that BDS's network variables do serve as proxies for spoke traffic in the manner hypothesized. For example, the results show that SPKPASS is an increasing function of network size, as measured by the number of 4-segment markets served. Given these results, BDS's findings are properly viewed as indirect evidence of the existence of economies of density.

4. Structural Estimation

We saw in the last section that fares at the city-pair level are inversely related to spoke traffic densities. Moreover, the appendix shows that spoke traffic is itself a function of network characteristics. These results strongly suggest that network operations have an important impact, via the density effect, on the cost of providing airline service. However, since the fraction of the cost savings passed on to passengers is unobserved, the strength of the density effect is unknown. Are most of the benefits passed on, so that economies of density are approximated by the observed fare effect? Or are much of the gains retained by the airlines, in which case the fare effect

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[24]BDS's main results are based on observations from the individual-fare sample where the fare class is YD (coach-discount) for all segments of the trip. Unreported estimates of the present model using that sample are similar to those in Table 2 (the sample has 9790 observations).

understates the strength of economies of density? The purpose of this section is to begin the task of answering these questions.

Unfortunately, information that would allow us to directly estimate a cost function at the spoke level is not available (accounting data, which is organized at the firm level, provides no information relevant to individual spokes or markets). As a result, estimation of the desired cost function must be based on a structural model of airline behavior. There are three components to a structural model of any industry: demand, cost, and the nature of oligopolistic interaction. As explained below, assumptions must be made in each of these areas to carry out the estimation. It should be clear that our results will be sensitive, at least to some extent, to the nature of these assumptions.

a. The structural model

Initially, we ignore demand heterogeneity across different groups of travellers (businessmen, vacationers, etc.), and assume that market demand is represented by a single demand function.[25] We also assume linearity, so that the inverse demand function for travel in market m is given by[26]

$$p_m = a_m + (1/b)q_m + \epsilon_m, \tag{1}$$

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[25]Reiss and Spiller (1989) estimate a model of airline demand which takes into account substitution between connecting and direct (nonstop) travel. Developing the present analysis along these lines would add substantial complications, as competition among differentiated products would have to be modelled. Reiss and Spiller's (1989) main focus, however, was on demand, while our emphasis is on costs. For that reason, we leave the elaboration of the demand side of our analysis for future research.

[26]To simplify terminology, we refer to directional routes as "markets" in the rest of the paper. A given nondirectional city-pair market, say ij, thus contains two "markets" under this definition: the market for travel from i to j and back, and the market for travel from j to i and back. The term "city-pair market," however, will continue to be used in a nondirectional sense.

where p_m is the fare, q_m is the number of round-trip passengers in the market, and ϵ_m is a normally distributed error term with mean zero and constant variance σ_ϵ^2. Note that the demand intercept a_m is market-specific (depending on income, tourism potential, etc.) while the (negative) slope 1/b is the same for all markets. As noted above, this formulation ignores the multiplicity of fares in a given market, which arises mainly because of price discrimination between business and vacation travellers. However, it will be seen below that (1) can be viewed as the aggregate demand function across such groups, with p_m representing the average fare in the market.

Regarding airline behavior, we assume that the carriers behave as if they play a Nash game in quantities. Since our data is a single-period cross-section of markets and firms, models of dynamic games cannot be estimated. Moreover, alternative one-period behavioral models such as marginal cost pricing or perfect collusion are not very compelling for the airline industry.[27] In any case, both Reiss and Spiller (1989) and Brander and Zhang (1990) find that the Cournot solution concept cannot be rejected in favor of models using more general conjectural variations. Imposing the Cournot assumption and letting q_{im} denote carrier i's traffic in market m, with $\Sigma_i q_{im} = q_m$, the carrier's marginal revenue in market m can be written as

$$MR_{im} = a_m + (1/b)(q_m + q_{im}) + \epsilon_m. \tag{2}$$

Carrier i's total cost function for operating the J spokes of its network is given by

[27]Marginal cost pricing is inconsistent with declining marginal costs, while monopoly pricing is inconsistent with previous empirical studies and casual empiricism on competitiveness in the industry.

$$c_{i1}(Q_{i1}) + c_{i2}(Q_{i2}) + \ldots + c_{iJ}(Q_{iJ}) + F_i, \tag{3}$$

where Q_{ij} is traffic on the jth spoke and F_i represents fixed costs, and where the spoke cost functions $c_{ij}(\cdot)$ satisfy $c_{ij}'' < 0$ with economies of density. If market m includes cities k and r, then using (3), the marginal cost of serving a passenger in the market is $c_{ik}'(Q_{ik}) + c_{ir}'(Q_{ir})$. When the spoke marginal cost function has the form $c_{ij}' = \gamma_{ij} + \beta Q^{\delta}_{ij}$, this expression becomes $\gamma_{ik} + \gamma_{ir} + \beta(Q^{\delta}_{ik} + Q^{\delta}_{ir})$. Consider the special case where marginal cost is linear ($\delta = 1$), which was discussed above. In this case, carrier i's marginal cost of serving a passenger in market m reduces to

$$MC_{im} = \alpha_{im} + \beta S_{im} + \omega_{im}, \tag{4}$$

where $S_{im} = Q_{ik} + Q_{ir}$ is the sum of traffic levels on the spokes connecting the market cities, $\alpha_{im} = \gamma_{ik} + \gamma_{ir}$, and where ω_{im} is a normal error term with mean zero and variance σ_ω^2 (ω_{im} and ϵ_m are assumed to be uncorrelated).[28] Note that while the intercept in (4) depends on the characteristics of both the carrier and the market (distance along the market spokes is important in the latter case), the marginal cost slope is the same across carriers and markets.

The carrier determines q_{im} by equating marginal revenue and marginal cost, which yields

$$a_m + (1/b)(q_m + q_{im}) + \epsilon_m = \alpha_{im} + \beta S_{im} + \omega_{im}. \tag{5}$$

Summing across the n_m carriers in the market,[29] (5) becomes

[28]Note that the market-specific shocks to carrier marginal costs are drawn from the same distribution. We model network-wide firm-specific shocks by letting the marginal cost intercept depend on the identity of the carrier; on this, see below.

$$n_m a_m + (1/b)(n_m q_m + q_m) + n_m \epsilon_m = n_m \bar{\alpha}_m + \beta n_m \bar{S}_m + \Sigma_{i \in m} \omega_{im}, \tag{6}$$

where the bars over the variables on the RHS indicate that these are mean values over the carriers in the market (the errors are summed across these carriers). Solving (6) for q_m and substituting into (1) yields the two reduced-form equations for the market quantity and fare:

$$q_m = \frac{b}{(1+n_m)} [n_m(\bar{\alpha}_m - a_m) + \beta n_m \bar{S}_m] + \phi_m \tag{7}$$

$$p_m = \frac{1}{1+n_m} [a_m + n_m \bar{\alpha}_m + \beta n_m \bar{S}_m] + \nu_m, \tag{8}$$

where

$$\phi_m = \frac{b(\Sigma_{i \in m} \omega_{im} - n_m \epsilon_m)}{1+n_m} \tag{9}$$

$$\nu_m = \frac{\Sigma_{i \in m} \omega_{im} + \epsilon_m}{1+n_m}. \tag{10}$$

Note that the variances of ϕ_m and ν_m are $\sigma_\phi^2 = b^2(n_m^2 \sigma_\epsilon^2 + n_m \sigma_\omega^2)/(1+n_m)^2$ and $\sigma_\nu^2 = (\sigma_\epsilon^2 + n_m \sigma_\omega^2)/(1+n_m)^2$ respectively, and that the correlation between ϕ_m and ν_m is $\rho = bn_m(\sigma_\omega^2 - \sigma_\epsilon^2)/\sigma_\phi \sigma_\nu (1+n_m)^2$.[30] Note also that (8) is linear in the fare, in

[29]Recall that MKTCOM in Section 3 counted other competitors in the market, regardless of whether they provided nonstop or 4-segment (connecting) service. Here, n_m is equal to the number of firms with connecting service (nonstop competitors are ignored). This approach involves an implicit assumption that connecting service is a different product than nonstop service.

[30]The issue of endogeneity of SPKPASS can be clarified with reference to (7) and (8). The first thing to note is that S_m can be determined by solving the reduced-form equations simultaneously across all markets, keeping track of which markets use which spokes. The solution will show that S_m depends on

contrast to the semi-log reduced-form specification of Section 3 (see below for further discussion of this point).[31]

If the spoke marginal cost functions are nonlinear (if δ above differs from unity), then the reduced-form equations must be modified. In particular, the expression $\beta n_m \bar{S}_m$ in (6) and (7) must be replaced by

$$\beta \, \Sigma_{i \in m}(Q^{\delta}{}_{imo} + Q^{\delta}{}_{imd}), \tag{11}$$

where Q_{imo} and Q_{imd} are carrier i's traffic levels on the spokes connecting the origin and destination cities of market m to the hub.

To estimate demand and marginal cost parameters from the above reduced-form equations, we proceed as follows. First, we let the demand and marginal cost intercepts be given by

$$a_m = a_o + a_1 INCORIG_m + a_2 TEMPDIF_m + a_3 MKTPP_m \tag{12}$$

and

$$\alpha_{im} = \alpha_{oi} + \alpha_1 DIST_{im} + \alpha_2 ORD_m + \alpha_3 DCA_m + \alpha_4 LGA_m + \alpha_5 JFK_m, \tag{13}$$

where α_{oi} is the carrier-specific component of the marginal cost intercept. After substituting (12) and (13) in (7) and (8),[32] we estimate the structural

the error terms ω_{im} and ϵ_m for all airline markets in the economy. Given that the error terms in (8) relate to a single market, correlation between $\bar{S}_m$ and these errors will be negligible as long as errors are uncorrelated across markets. Treating S_m as exogenous in estimating (7) and (8) is then appropriate. This argument can also be used to justify the use of OLS in the fare regressions of Section 3.

[31]The error terms for observations representing travel in different directions in a given city-pair market might be correlated, a possibility that we ignore. BDS found that taking such correlation into account had little effect on their results.

parameters by maximum likelihood, taking the cross-equation parameter restrictions and the correlation between the equations' errors into account. Nonlinear ordinary least squares estimates would be consistent but inefficient (inefficiency results from ignoring the heteroscedasticity and correlation of the errors in (9) and (10)).[33]

As noted above, the model as presented appears to ignore demand heterogeneity in the market. However, recognizing the presence of heterogeneity may leave the basic structure unchanged. For example, suppose that all markets have K different groups of travellers, each with a different demand intercept a_m^k, k=1,2,...,K, in (1) (demand slopes are assumed to be the same, but the errors ϵ_m^k are now group-specific). Then, assuming airlines can segment the market by the usual kinds of fare restrictions, they will equate marginal revenue to marginal cost for each type of traveller, leading to K sets of equations (7) and (8) (a_m, ϕ_m, ν_m are now indexed by k). These equations can be collapsed by first summing (7) across k, which yields an equation with total market traffic ($\Sigma_k\, q_m^k$) on the left-hand side, the average demand intercept ($\Sigma_k\, a_m^k/K$) on the right, and with b replaced by bK. Similarly, (8) is collapsed by averaging, which yields an equation with the average fare $\Sigma_k\, p_m^k/K$ on the left-hand side and $\Sigma_k\, a_m^k/K$ on the right. The new equations are thus the ones that would result from replacing (1) by $p_m = \Sigma_k\, a_m^k/K + (1/bK)q_m$ and interpreting

[32]Note that, using (13),

$$\bar{\alpha}_m = \alpha_1\overline{DIST}_m + \alpha_2 ORD_m + \alpha_3 DCA_m + \alpha_4 LGA_m + \alpha_5 JFK_m + (1/n_m)\Sigma_{i\in m}\alpha_{oi}CAR_{im},$$

where $\overline{DIST}_m$ is average distance for the carriers in market m and CAR_{im} is a variable that assumes the value one if carrier i serves market m and zero otherwise. Note that these latter variables are not dummies in the sense of Section 3 since several of the variables can equal unity for a given market observation.

[33]The estimation was carried out using the DFP algorithm of GQOPT. Nonlinear OLS and maximum likelihood estimation in fact yield similar results.

p_m in (8) as average fare in the market. It is easy to see, however, that this equation gives the inverse of the aggregate market demand curve. Our estimates can thus be viewed as giving the slope and intercept of this aggregate curve under conditions of demand heterogeneity.

Given this discussion, the heterogeneity of actual fares is collapsed by taking a simple average across carriers in each market of the unweighted carrier-specific mean fares already computed in the mean-fare data set. This "mean market" fare plays the role of p_m above. In addition, passengers on all carriers are summed within each market and the result multiplied by 10 to get q_m.[34] The data set that results from this averaging procedure has 5431 observations.[35]

b. Results

In estimating the model, we allowed the spoke marginal cost function to take a nonlinear form, with the exponent δ different from unity. Since the resulting estimate of δ was close to one, we also computed results for the linear case. The first column of Table 4 shows the key estimated coefficients for the nonlinear specification, while the second column shows the linear results. The demand coefficients are nearly identical for the two specifications. The coefficients a_1, a_2, and a_3 of the three demand-shift variables are all significantly positive, indicating that demand for air travel

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[34]Recall that the DB1A data is drawn from a 10% sample. The average number of passengers per market is 170 in this "mean-market" data set, and the average fare is $299.

[35]In generating this data set, we dropped the restrictions in footnote 16 (this was done to conserve all possible information for each market). However, we eliminated markets for which the origin was a concentrated hub airport (see BDS for a list). As argued by Borenstein (1988, 1989), in those markets, dominant carriers command a fare premium over fringe carriers, making inappropriate our assumption of homogeneous products.

is high when a market is large, has a high-income origin city, or has high tourism potential (the demand intercept (eq. (12)) evaluated at sample means equals 414.52 and 414.42 for the two cases).[36] In addition, the reciprocal of the inverse-demand slope is negative and strongly significant. Among the marginal cost estimates, the DIST coefficient is significant and positive in both specifications, and spoke traffic's exponent in the nonlinear specification is equal to 1.109. While this value is significantly different from unity on the basis of a t-test, its closeness to one means that the linear specification can be adopted with little loss of accuracy.[37] Since the multiplicative β coefficient is significantly negative under both specifications, marginal cost is decreasing in spoke traffic in both cases. The estimates thus confirm the existence of economies of density at the structural level, reinforcing the results of the fare regressions of Section 3. The coefficients of the carrier and airport variables in the marginal cost function are not reported,[38] but the marginal cost intercept (eq. (13)) evaluated at sample means equals 218.91 and 288.45 in the two cases. The Table also shows the estimated standard deviations of the demand and marginal cost shocks.

Elasticities are reported in Table 5. In both specifications, the price

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[36]Since INCORIG, TEMPDIF, and MKTPP are market specific, sample means of these variables are taken from the mean-market data set. Means of the marginal cost variables are taken from the mean-fare data set, which is carrier-specific.

[37]Note that since the log likelihoods for the linear and nonlinear models differ by less than one, the linear model cannot be rejected against the nonlinear alternative using a likelihood ratio test (this test and the t-test need not give the same answer in a nonlinear setting).

[38]Major carriers with marginal costs lower than American's are Braniff, America West, Midway, New York Air, and Air Cal. Carrier-variable coefficients are larger than the American value of 129.2, indicating higher costs, for all the other major airlines.

elasticity of demand evaluated at sample means is a plausible -2.5, while the income elasticity is 0.6.[39] The TEMPDIF elasticity is small, while the MKTPP elasticity of 0.3 indicates that demand increases less rapidly than the size of the market. The elasticity of marginal cost with respect to distance equals is near 0.3, a number close to the distance elasticity in the earlier fare regressions. The major result of Table 5, of course, concerns the strength of economies of traffic density, which is revealed by the elasticity of marginal cost with respect to SPKPASS. The elasticity value is -0.449 in the nonlinear specification and -0.468 in the linear case, showing that marginal cost falls by about 4.5% for every 10% increase in spoke traffic.[40] This density effect is more than twice as strong as that estimated by Caves et al., whose 0.80 cost elasticity with respect to traffic translates into a marginal cost elasticity of -0.20.

Using (8) from the linear specification, we can compute the extent to which cost savings from higher traffic densities are passed on to passengers in lower fares, addressing the question raised at the beginning of this section. Suppose first that a single carrier in a market experiences a one-standard-deviation increase in spoke traffic.[41] Using (8), the result is a fare decrease of 6% (evaluated at sample means). If, instead, each carrier in the market experiences a one-standard-deviation increase in spoke traffic, (8) shows that fares fall by 9%.[42] On the cost side, our estimates suggest that a one-

[39]Our price elasticity is of roughly the same order of magnitude as the -1.6 value used by Brander and Zhang (1990), which represents their judgement as to the best estimate from the prior literature.

[40]These values give the elasticity of marginal cost for a single spoke with respect to traffic on that spoke.

[41]Recall that this increase is about 33,000 passengers per quarter.

standard-deviation increase in spoke traffic reduces marginal cost by 24% (this follows because traffic rises by nearly 50% and because the estimated linear elasticity is -0.47). Therefore, evaluating at sample means, our results suggest that somewhat less than half (9% vs. 24%) of a cost reduction resulting from a symmetric increase in traffic across carriers is passed on to passengers in the form of lower fares.

The 6% fare reduction from a single-carrier increase in spoke traffic is more than three times as large as the 1-2% decline computed in Section 3, and it is important to isolate the reason for this discrepancy. The discrepancy is not due to the different functional forms of the regressions (semi-log in Section 3 vs. linear here) nor to the use of cross-equation restrictions in estimating the fare equation (8).[43] Aggregation up to the market level is also not the source of the discrepancy (recall that the earlier observations were carrier- rather than market-specific).[44] The discrepancy is thus a consequence of the one remaining difference between the specifications: the nonlinear form of the structural price equation, in which average spoke traffic appears multiplied by the term $n_m/(1+n_m)$. This functional form, however, is implied by the Cournot model. If that model is correct, then we could conclude that the smaller fare impacts from the earlier ad-hoc regressions are the result of specification error. In any case, it is clear that the quantitative impact of

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[42]The average number of carriers per market is 1.46.

[43]Linear versions of the regressions of Section 3 yield the same 1-2% fare impacts from a one-standard-deviation increase in spoke traffic. Also, when (8) is estimated independently by OLS, ignoring the cross-equation restrictions, the results still yield a large 5.3% fare impact.

[44]If, using the mean-market data set, average market fare is regressed on the average spoke traffic of carriers in the market (in an equation analogous to those in Table 2), the implied fare reduction from a one-standard-deviation traffic increase is 1.1%, which lies in the earlier range.

spoke traffic on fares will be sensitive to the specification of the estimating equation.

In the next section of the paper, we use the structural estimates to simulate the impact of an airline merger.

5. Merger Simulations

The TWA-Ozark and Northwest-Republic mergers, which created monopoly hub airports at St. Louis and Minneapolis respectively, have generated much concern among policy makers. The concern has centered on monopolistic exploitation of passengers originating or terminating at the hub airports, who now have little choice among carriers and are thus likely to pay higher fares. There has been partial confirmation of this prediction in several studies [see Borenstein (1990), U.S. General Accounting Office (1988), Department of Transportation (1989), and Werden, Joskow, and Johnson (1989)]. Elsewhere, however, we have pointed out that connecting passengers, who are not subject to monopoly power given a choice of hubs, may actually benefit from the merger (see BDS). The reason is that the merger creates a larger, more densely-travelled network, and this effect, together with continued competition in the 4-segment markets, may lead to lower fares for connecting passengers.

a. The setup

Using the structural estimates from the linear specification, we can simulate the effects of a TWA-Ozark-type merger to evaluate these predictions.[45] We consider several scenarios where three or more competing carriers serve a common set of J cities out of several hubs, as shown in Figure 2. In case I, two carriers (#1 and #2) operate out of hub A, while another carrier (#3) serves the same endpoints out of hub B (the Figure uses J = 3). Residents of

[45]For an earlier study of the effects of mergers, see Carlton, Landes and Posner (1980).

each endpoint have travel demands to every other endpoint and to each of the hub cities, and residents of the hub cities demand travel to each of the endpoints (for simplicity, there is no demand for travel between the hubs). Using the demand and marginal cost functions from the linear case of Section 4, we simulate the effect of a merger of the two hub-A carriers.

Case II differs from Case I in that hub B supports two carriers instead of one (#4 is added). In Case III, the two non-merging carriers operate out of different hubs, B and C (there are now travel demands from each endpoint to each of the three hubs). The impact of a merger of the hub-A carriers is again simulated. The common element in each case is that the merger partners gain monopoly power over traffic originating or terminating at hub A. Competition is reduced by the merger, but not eliminated, in the 4-segment (connecting) city-pair markets.[46]

Before providing a detailed explanation of the simulations, several caveats are in order. The first relates to our assumption that the merging airlines compete in all markets served via hub A. This assumption, which is made to preserve the model's symmetry (and its computational simplicity), means that the loss of competition in the 4-segment markets is greater than that experienced in actual mergers. For example, TWA and Ozark competed in only 10% of the 4-segment markets served through St. Louis, while Northwest and Republic competed in 18% of the 4-segment markets served through Minneapolis. Given this difference, our results may substantially overstate the anticompetitive effects of a merger. In addition, our cost estimates do not include the fixed costs of network operations. If redundant fixed costs are eliminated by the merger, the result is a welfare gain that is not captured by our calculations.

[46]See Brueckner and Spiller (1991) for an analysis of the effect of localized competition within a network (and the effect of mergers that eliminate such competition) using a model similar to the one presented here.

On both these counts, our simulations may understate any welfare gains associated with a TWA-Ozark-type merger.

In the simulations, we assume that each carrier is identical by evaluating the marginal cost intercept α_{im} at the sample mean values of the carrier dummy variables (the slot-control dummies are set to zero). In addition, all connecting trips are assumed to be the same length, equal to the sample mean value of DIST.[47] Using the resulting common value of α, the spoke marginal cost function is then $(\alpha/2) + \beta Q$ for each carrier, where Q represents traffic on a single spoke.

To generate demand, we assume that the demand function estimated in Section 4 applies to direct as well as connecting flights. We evaluate the demand intercept a_m for each market using sample average values of INCORIG and TEMPDIF. For connecting markets, we set MKTPP equal to the sample mean value, while for hub markets, MKTPP is adjusted to reflect the typically larger population of the hub.[48] The common value of a_m for the connecting markets is denoted a, while the common value for the hub markets is a_H.

Consider now the optimization problems faced by the carriers under case I. Let q_i denote carrier i's traffic ($i = 1,2,3$) in each of its $J(J-1)$ connecting markets (note that markets are treated as directional for consistency with the empirical work). Carrier i's total revenue from the connecting markets is then $J(J-1)q_i[a+k(q_1+q_2+q_3)]$, where $k \equiv 1/b$ is the demand slope from (1). Note that $a + k(q_1+q_2+q_3)$ gives the fare in a connecting market, each of which is served by all three carriers. Similarly, let q_{Hi}

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[47]This is literally impossible given the different locations of the hubs, but seems to be a safe approximation.

[48]In this case, MKTPP is set equal to the sample average of $[(POP_i POP_{hub})^{1/2} + (POP_j POP_{hub})^{1/2}]/2$, which approximates the population potential of a typical hub market (i and j denote the endpoints of 4-segment markets).

denote carrier i's traffic ($i = 1,2$) in each of its 2J hub markets (these are markets where one endpoint is hub A). Carrier i's total revenue from the hub markets is then $2Jq_{Hi}[a_H+k(q_{H1}+q_{H2})]$, $i = 1,2$. Note that $a_H + k(q_{H1}+q_{H2})$ is the fare in a hub-A market, each of which is served by carriers 1 and 2. Finally, since total traffic on each spoke consists of traffic in 2(J-1) connecting markets and 2 hub markets, carrier i's cost ($i= 1,2,3$) of operating each of its J spokes is $c(2(J-1)q_i+2q_{Hi})$. Profit for carriers 1 or 2 is then

$$J(J-1)q_i[a+k(q_1+q_2+q_3)] \quad + \quad 2Jq_{Hi}[a_H+k(q_{H1}+q_{H2})] \quad - \quad Jc(2(J-1)q_i+2q_{Hi}), \tag{14}$$

for $i = 1,2$ (fixed cost is ignored). Carrier 3 differs from 1 and 2 in that it alone serves the hub-B markets. The fare in these markets is $a_H + kq_{H3}$ and total revenue is $2Jq_{H3}(a_H+kq_{H3})$. Carrier 3's profit can then be written

$$J(J-1)q_3[a+k(q_1+q_2+q_3)] \quad + \quad 2Jq_{H3}(a_H+kq_{H3}) \quad - \quad Jc(2(J-1)q_3+2q_{H3}). \tag{15}$$

To find the premerger equilibrium, first-order conditions are derived for q_i and q_{Hi}, $i=1,2,3$, and the conditions are solved algebraically (c' is represented by the above spoke marginal cost function). To find the postmerger equilibrium, the first-order conditions are solved again under the assumption $q_2 = q_{H2} = 0$. The equilibria are then compared. The profit functions for cases II and III are easy extensions of (14) and (15).

<u>b. Simulation results</u>

Table 6 presents the simulation results for the three merger scenarios under the assumption that the number of endpoints served is 80. Consider Case I first. The numbers of carriers operating through the hubs are listed under #A, #B, and #C; q_i denotes carrier i's traffic in each connecting market, q_{Hi} denotes the carrier's hub-market traffic; Q_i denotes the carrier's spoke traffic (this is traffic on an individual spoke); q denotes total traffic in the connecting markets ($\Sigma_i q_i$); p is the fare in each connecting market; and p_{H12} and p_{H3} are the fares in the hub markets for carriers 1 and 2 and carrier 3 respectively (q_2, q_{H2}, and Q_2 are all zero in the second line).[49] The results for Case I show that the merger leads to a slight fare increase in the connecting markets, and that it raises the fare to hub A substantially while slightly reducing the fare to hub B. Total quantities in each type of market show opposite movements. On balance, consumer surplus falls as a result of these market impacts while total profit for all carriers rises.[50] Since the profit increase is slightly larger than the reduction in surplus, net benefit rises slightly as a result of the merger.[51]

The key to these results is that the merger has differential effects on competition in the hub and connecting markets. Passengers originating or terminating at hub A now face a monopoly carrier, while connecting passengers still enjoy the benefits of competition (the number of competitors, however, is reduced from 3 to 2 in the connecting markets). The merger also leads to higher spoke traffic levels, and the resulting reduction in marginal cost interacts with the changes in competition to determine fare impacts. For hub-A passengers, the total elimination of competition overwhelms the effect of lower

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[49]Variables for carrier 4 appear in Cases II and III, but these are self-explanatory.

[50]The profit of carrier #3 rises substantially, while the merged carrier earns profit somewhat higher than the combined premerger profits of carriers #1 and #2.

[51]It is worth noting that the second-order condition for the carriers' maximization problems, which requires $-\beta < -k/(2J-1)$, is satisfied under our parameter values (this condition says that economies of density must be bounded by a quantity that depends on the demand slope and the number of endpoints served).

costs, and fares rise substantially. This is the impact emphasized by merger critics. However, for connecting passengers, the effects of the cost reduction and the loss of competition nearly offset one another, leading to a slight increase in fares.[52] This outcome is qualitatively different from the one predicted by BDS, but given the potential bias in our simulations and given that BDS predicted only a 1 - 2% decline in connecting fares, the effects may be indistinguishable.[53] On balance, then, a TWA-Ozark-type merger appears to benefit the airlines while reducing consumer welfare, with the big losers being the passengers travelling to or from the monopoly hub.

In Cases II and III, the merging carriers face additional competition, either through hub B or a third hub. The outcomes in these cases, however, are qualitatively similar to case I. Connecting fares rise slightly, hub-A fares rise substantially, hub-B (and hub-C fares in case III) fall slightly, surplus falls, profit rises, and net benefit increases slightly. This shows that even when more initial competitors are added to the connecting markets, the effect of lost competition is still strong enough to offset the merger's cost reduction, leading to slightly higher connecting fares. This conclusion holds independently of whether the additional carrier operates from hub B or from hub C.

Although the merger scenarios are complicated by the existence of multiple markets, the principle underlying the outcomes is familiar from standard oligopoly models: With increasing returns, a merger reduces costs

[52]Fares to hub B fall because the rise in carrier 3's spoke traffic as a result of the loss of a competitor in the connecting markets lowers marginal cost while the extent of competition in the hub-B markets (i.e., none) remains unchanged.

[53]Borenstein (1992) provides estimates of the impact of the Northwest-Republic merger on connecting fares at Minneapolis, and his results also fall in the 1 - 2% range.

while eliminating competition. The merger will be welfare-improving if the first effect dominates the latter, an outcome that requires increasing returns to be "strong." Our simulations reflect this principle, and the slight welfare gains that we find testify to the strength of our estimated economies of density.

A final point should be made regarding the realism of the simulations. The magnitudes of fares, market traffic levels, and spoke traffic levels are all similar to actual levels in the data.[54] While this may not be surprising given that the simulations are based on estimated coefficients, it should be remembered that the simulated values come from algebraic solution of a symmetric Cournot model. Thus, the fact that the numbers are realistic is encouraging both with respect to the accuracy of the estimates and the realism of our modelling of airline competition.

6. Conclusion

This paper has provided the first evidence linking marginal costs and fares to traffic densities on the spokes of an airline network. Our results confirm the existence of the economies of density first identified by Caves *et al*. (1984) while showing that the gains from density are partly passed on to passengers in lower fares. This finding highlights a potential source of the benefits of deregulation. By allowing the airlines to reorganize their route

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[54]Recall that the average connecting fare is close to $300 and that average traffic in the connecting markets is 170. The simulated spoke traffic levels should be compared to the AVGSPKPAS values in Table A-1 in the appendix, not to the much higher sample average values (see footnote 21). It should be noted that since the simulated networks have a U value of 1.0, the number of city-pair markets served is vastly larger than any in Table A-1 (over 6000). Real networks, however, serve many large markets, which generate much more traffic than any in the simulation, while connections are not observed (or occur at low levels) in many small markets. Therefore, the excessive number of connections made in the simulated network may not lead to an overstatement of total traffic flows.

structures to increase traffic densities, deregulation led to lower costs, and this effect (together with freer competition) may have helped to reduce fares.

The paper uses a structural approach to estimate the strength of economies of density. Our results reveal a density effect stronger than that identified by Caves et al. (1984). Using this estimate, along with estimates of the parameters of demand, the paper then simulates the effect of airline mergers and finds that the gain from higher traffic density seems to outweigh the loss from reduced competition, leading to a slight increase in social welfare. This welfare gain, however, is accompanied by sizable reduction in consumer surplus.

Appendix

a. Network characteristics

Information about the structure of hub-and-spoke networks in the fourth quarter of 1985 is given in Table A-1, which repeats information from BDS.[55] The first column presents a measure of network size, denoted NTWCITP4, which equals the total number of 4-segment city-pair markets served by each network. The Table shows that network sizes, as represented by NTWCITP4, vary considerably, with American's Dallas-Ft. Worth network (which serves 1564 4-segment city-pair markets) being the largest. Each city-pair market counted in NTWCITP4 represents a connection, via the hub, between two of the endpoints served by the network. The number of such endpoints, denoted POINTS, is shown in column two of Table A-1. A measure of the network's success in connecting these endpoints is one index of its performance, and such a measure (the network "utilization rate," denoted U) is shown in column three. U equals NTWCITP4 (actual connections) divided by POINTS*(POINTS-1)/2 (potential connections), and its value is highest for America West's Phoenix network (.606) and lowest for United's Chicago-O'Hare network (.155). Competition within a network is measured by NTWCOM4, which equals the fraction of the network's 4-segment markets in which the carrier faces at least one competitor (competition could come from 4-segment or nonstop service). Eastern's Kansas City network has competition in all of its 4-segment markets, while United faces a competitor in just 40% of the markets served by its San Francisco network. Network average population potential (NTWAVGPP) is a measure of the average size of the markets served by a network.[56] Eastern's Kansas City

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[55]The first five columns of the Table come from manipulation of the DB1A route information; the last column is based on the Service Segment Databank DB27R.

[56]Recall that population potential for city-pair market ij is equal to

network serves the largest markets on average, while Frontier's Denver network serves the smallest markets. Finally, the last column of Table A-1 presents data for AVGSPKPAS, which equals the average quarterly traffic level on individual spokes emanating from the hub of each network.[57] Delta's Atlanta network has the highest AVGSPKPAS value (36,111 passengers per quarter), while Ozark's St. Louis network has the lowest (12,730 passengers per quarter). Our main hypothesis suggests that a network (like Delta's) with high spoke traffic densities should have low costs per passenger, and thus low fares for typical trips within it.

b. The determinants of SPKPASS

BDS test for the presence of economies of density using an indirect approach where network characteristics appear in the reduced-form fare regression in place of spoke traffic levels. They hypothesize that if a network is large (if NTWCITP4 is large), then traffic levels on its spokes will be high and fares in any given 4-segment market will be low, other things equal (traffic levels are high because a large network offers many destinations). Similarly, if the network experiences competition in many of its markets (if NTWCOM4 is high), then the resulting traffic leakage will raise cost per passenger on a typical spoke. Holding competition in a given market constant, these higher costs then lead to higher fares in the market. BDS also discuss the relevance of two other variables: ORIGSHR, which equals the fraction of the network's 4-segment city pairs that include the market's origin city, and

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$(POP_i POP_j)^{1/2}$, where POP is city population measured in 10,000s. This quantity is summed across all city pairs served by the network and divided by NTWCITP4 to arrive at network average population potential, NTWAVGPP.

[57]AVGSPKPAS is computed by deleting spokes that had fewer than 250 passengers in the quarter (these are evidently not true spokes but instead represent sporadic service or aircraft diversions).

DESTSHR, which equals the fraction of the network's 4-segment city pairs that include the market's destination city. Holding NTWCITP4 fixed, a high value of ORIGSHR (DESTSHR) means that the spoke between the origin (destination) and the hub is heavily travelled, resulting in a lower cost per passenger on that spoke and lower fares in the market.[58] In BDS's regression, all of the above network variables have the anticipated effect on fares, providing indirect evidence of the existence of economies of density.

As explained in the text, BDS offer no evidence on the connection between spoke traffic and network characteristics, so that key assumptions in their argument remain untested. To verify these assumptions, Table A-2 presents the results of a regression of SPKPASS on the above network characteristics as well as market demand variables and carrier dummies. The Table shows that spoke traffic in a given city-pair market is indeed an increasing function of network size and the extent of connections between the origin and destination cities of the market and the rest of the network (the coefficients of NTWCITP4, ORIGSHR, and DESTSHR are significantly positive). Using our previous example, these findings indicate that traffic on the CMI-ORD and CLE-ORD spokes of United's O'Hare network will be higher than the traffic levels on spokes connecting similar endpoint cities to the hub of a smaller network. In addition, holding network size fixed, the traffic level on the spoke to some endpoint ZZZ otherwise similar to CMI will be lower than on the CMI-ORD spoke if ZZZ is included in fewer network city pairs than is CMI (the value of SPKPASS will thus be lower for a market like ZZZ-CLE than for CMI-CLE).

Table A-2 also shows that a high degree of 4-segment competition in the markets served by the network (a high NTWCOM4) means lower spoke traffic in any given market. Thus, traffic on the CMI-ORD and CLE-ORD spokes of United's network will be higher than traffic on the spokes connecting CMI and CLE to the

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[58]Mean values of these variables are around 0.05.

hub of a similar-sized network that experiences more generalized competition (American's ORD network, for example; see Table A-1). Table A-2 also shows that SPKPASS is decreasing in distance and increasing in MKTPP, INCORIG, and INCDEST (the latter variable is per capita income for the city-pair market's destination city). Thus, when the endpoint cities of a market are large and have high incomes, traffic on the spokes connecting them is high.

The carrier dummies in Table A-2 tell an interesting story. They indicate that holding network characteristics fixed, the carriers achieve varying decrease of success relative to American, the default carrier, in generating traffic within their networks. Nearly all carriers do a worse job of traffic generation than American, with the only exceptions being Continental, America West, and United. These differences could be due to the effects of frequent flier programs, which build carrier loyalty and hence traffic, to the carrier's skill in choosing which cities to serve out of its hub, and to the effect of pricing policies (low fares help build network traffic).

Table 1

VARIABLE DEFINITIONS

SPKPASS:	The sum of the spoke traffic levels on the spokes connecting the origin and destination to the hub
DIST:	One-way flight distance for the market
ORD, LGA, JFK, DCA:	Dummy variables taking the value one if origin or destination is one of the given airports
MKTPP:	The market's population potential (the square root of the product of the market city populations)
INCORIG:	Per capita income for the origin city
TEMPDIF:	The mean January temperature at the destination minus the mean temperature at the origin
MKTCOM:	The number of carriers competing with the given carrier in the market
MKTPCOM:	The number of carriers serving both endpoints of the market without serving the market itself
FARE:	The dollar round-trip fare

Appendix variables:

NTWCITP4:	The number of 4-segment city-pair markets connected by the network
POINTS:	The number of non-hub cities served by the network
U:	The network's utilization rate, equal to NTWCITP4 divided by POINTS*(POINTS-1)/2
NTWCOM4:	The fraction of the network's 4-segment city-pair markets where at least one competitor is present
NTWAVGPP:	The average population potential of the network's 4-segment city-pair markets
AVGSPKPS:	Average traffic on individual spokes of various airline networks
ORIGSHR:	The fraction of the network's 4-segment city-pair markets that include the origin city
DESTSHR:	The fraction of the network's 4-segment markets that include the destination city

Table 2

REDUCED-FORM REGRESSION RESULTS

(Dependent variable is log FARE; t-statistics in parenthesis)

Variable/Sample	Individual-fare	Mean-fare	Mean-fare
INTERCEPT	2.772	3.896	3.785
	(42.81)	(53.72)	(52.90)
SPKPASS	-0.000000275	-0.000000367	-0.000000586
	(2.35)	(2.46)	(3.97)
LDIST	0.306	0.264	0.283
	(39.60)	(28.81)	(31.58)
MKTPP	-0.0000512	0.0000428	-0.000906
	(1.61)	(1.09)	(2.32)
INCORIG	0.00000290	0.00000451	0.00000215
	(1.08)	(1.40)	(0.67)
TEMPDIF	-0.00106	-0.00109	-0.00112
	(7.78)	(6.46)	(6.60)
MKTCOM1	-0.0792	-0.0713	-0.0795
	(8.18)	(6.38)	(7.12)
MKTCOM23	-0.0502	-0.0593	-0.0663
	(10.55)	(10.21)	(11.48)
MKTCOM4+	-0.00420	-0.00415	-0.00230
	(2.87)	(2.19)	(1.22)
MKTPCOM	-0.0184	-0.0195	**
	(9.52)	(8.19)	
R^2	.2486	.2642	.2577

obs=13,308 for individual-fare sample; obs=7732 for mean-fare sample

Table 3

AIRPORT AND CARRIER DUMMY COEFFICIENTS

(Estimates are for the regression in column (2) of Table 2; t-statistics in parentheses)

ORD	0.0446	MIDWAY	-0.126
	(2.27)		(3.60)
LGA	-0.0312	NORTHWEST	-0.00603
	(1.46)		(0.20)
JFK	-0.0906	NEW YORK AIR	-0.216
	(1.53)		(3.64)
DCA	0.0558	AIR CAL	-0.522
	(2.84)		(4.40)
US AIR	0.0285	OZARK	-0.00810
	(1.62)		(0.28)
ASPEN	-0.196	PIEDMONT	-0.135
	(3.28)		(7.58)
CONTINENTAL	-0.0230	REPUBLIC	0.0830
	(1.30)		(4.68)
DELTA	0.240	TRANS WORLD	0.0204
	(16.26)		(1.17)
EASTERN	0.0600	UNITED	0.122
	(3.71)		(7.74)
FRONTIER	-0.0730	EMPIRE	-0.181
	(3.05)		(2.75)
AMERICA WEST	-0.224	FLORIDA EXPRESS	-0.234
	(8.84)		(5.04)
BRANIFF	0.0704	AIR WISCONSIN	0.0676
	(0.85)		(0.60)
PAN AM	-0.0000266	WESTERN	0.0712
	(0.00)		(3.34)

Table 4

MAXIMUM-LIKELIHOOD STRUCTURAL ESTIMATES

(mean-market sample (obs=5431); asymptotic t-statistics in parentheses)

DEMAND COEFFICIENTS

	Nonlinear MC	Linear MC
a_0 (intercept)	299.8	300.8
	(66.21)	(109.16)
a_1 (INCORIG)	0.00732	0.00721
	(13.69)	(15.40)
a_2 (TEMPDIF)	0.971	0.967
	(8.66)	(8.28)
a_3 (MKTPP)	0.290	0.290
	(14.29)	(13.69)
b (slope)	-1.482	-1.483
	(75.26)	(71.60)
σ_ϵ	174.3	174.2
	(78.52)	(76.02)

MARGINAL COST COEFFICIENTS

	Nonlinear MC	Linear MC
α_{01} (American intercept)	127.8	129.2
	(18.19)	(16.89)
α_1 (DIST)	0.0506	0.0500
	(18.14)	(16.18)
β (spoke traffic multiplicative)	-0.000388	-0.00137
	(2.73)	(16.58)
δ (spoke traffic exponent)	1.109	1.0
	(36.46)	.
σ_ω	144.8	144.8
	(105.71)	(92.11)
log likelihood	-56157	-56158

(coefficients of the slot-control and carrier variables are not reported)

Table 5

STRUCTURAL ELASTICITIES

(evaluated at sample means)

DEMAND

	Nonlinear MC	Linear MC
Price:	-2.495	-2.497
INCORIG:	0.616	0.608
TEMPDIF:	0.015	0.015
MKTPP:	0.336	0.336

MARGINAL COST

	Nonlinear MC	Linear MC
DIST:	0.310	0.311
spoke traffic	-0.449	-0.468

Table 6

MERGER SIMULATIONS

CASE I

#A	#B	#C	q_1, q_2	q_{H1}, q_{H2}	Q_1, Q_2	q_3	q_{H3}	Q_3	q	p	PH12	PH3	Net benefit*	Profit	Surplus
2	1	0	55	149	9022	57	223	9441	167	$302	$232	$282	$103.26 m	$36.11 m	$67.15 m
1	1	0	80	227	13039	80	227	13039	160	$307	$280	$280	$106.15 m	$46.52 m	$59.63 m

CASE II

#A	#B	#C	q_1, q_2	q_{H1}, q_{H2}	Q_1, Q_2	q_3, q_4	q_{H3}, q_{H4}	Q_3, Q_4	q	p	PH12	PH34	Net bft.	Profit	Surplus
2	2	0	43	147	7078	43	147	7078	172	$299	$234	$234	$101.99 m	$29.78 m	$72.21 m
1	2	0	57	223	9441	55	149	9022	167	$302	$282	$232	$103.26 m	$36.11 m	$67.15 m

CASE III

#A	#B	#C	q_1, q_2	q_{H1}, q_{H2}	Q_1, Q_2	q_3, q_4	q_{H3}, q_{H4}	Q_3, Q_4	q	p	PH12	PH34	Net bft.	Profit	Surplus
2	1	1	42	147	6956	44	221	7371	172	$298	$234	$284	$108.49 m	$35.49 m	$73.00 m
1	1	1	56	223	9280	56	223	9280	168	$301	$282	$282	$109.90 m	$41.89 m	$68.01 m

*Net benefit, Profit, and Surplus are in millions of dollars.

(Numbers may not add due to rounding; $q_2 = q_{H2} = Q_2 = 0$ in the second row of each case)

Table A-1

NETWORK CHARACTERISTICS (4th QUARTER 1985)

Hub/Carrier	NTWCITP4	POINTS	U	NTWCOM4	NTWAVGPP	AVGSPKPS
Atlanta/Delta	1368	86	.374	.701	113.1	36,111
Atlanta/Eastern	1306	91	.319	.779	131.5	28,030
Baltimore-Wash./Piedmont	214	47	.198	.692	130.2	12,450
Charlotte/Piedmont	716	59	.418	.588	127.4	22,418
Dayton/Piedmont	158	33	.299	.665	135.4	13,453
Denver/Continental	307	44	.325	.932	204.4	26,171
Denver/Frontier	498	50	.407	.673	75.2	15,463
Denver/United	635	82	.191	.800	140.6	18,762
Dallas-Ft. Worth/American	1564	101	.310	.650	134.7	34,740
Dallas-Ft. Worth/Delta	402	55	.271	.948	152.4	25,434
Detroit/Republic	528	61	.289	.642	156.2	18,350
Houston/Continental	325	44	.344	.794	170.2	25,945
Kansas City/Eastern	125	39	.169	1.000	291.1	14,627
Chicago (Midway)/Midway	64	19	.374	.984	252.7	16,056
Memphis/Republic	668	57	.419	.704	134.2	16,987
Minneapolis/Northwest	242	42	.281	.740	183.4	18,340
Minneapolis/Republic	480	59	.281	.429	81.7	15,021
Chicago (O'Hare)/American	758	78	.252	.815	174.1	25,876
Chicago (O'Hare)/United	1033	116	.155	.754	151.4	26,601
Philadelphia/US Air	144	42	.167	.507	113.0	18,305
Phoenix/America West	140	22	.606	.700	86.7	33,622
Pittsburgh/US Air	1243	81	.384	.526	135.2	23,662
San Francisco/United	133	37	.200	.398	97.7	29,660
Salt Lake City/Western	537	52	.405	.611	115.6	15,611
St. Louis/Ozark	445	54	.311	.544	111.4	12,730
St. Louis/TWA	756	63	.387	.952	196.0	24,911

Table A-2

THE DETERMINANTS OF SPKPASS

(Dependent variable is SPKPASS; mean-fare sample (obs=7732); t-statistics in parentheses)

INTERCEPT	68700	US AIR	-42362	AIR CAL	-55922
	(10.96)		(32.46)		(6.45)
NTWCITP4	48.9	ASPEN	-76927	OZARK	-22095
	(38.01)		(14.78)		(9.42)
ORIGSHR	110720	CONTINENTAL	11909	PIEDMONT	-18242
	(11.97)		(7.67)		(11.90)
DESTSHR	136027	DELTA	-2427	REPUBLIC	-22904
	(14.16)		(2.29)		(15.10)
NC4COM	-23513	EASTERN	-17354	TRANS WORLD	-146
	(7.01)		(14.99)		(0.10)
LDIST	-10079	FRONTIER	-13745	UNITED	4547
	(16.47)		(7.31)		(3.63)
MKTPP	80.8	AMERICA WEST	32677	EMPIRE	-61975
	(38.26)		(15.29)		(12.51)
INCORIG	1.62	BRANIFF	-55956	WESTERN	-16615
	(7.14)		(9.06)		(9.67)
INCDEST	1.21	PAN AM	-23522	FLORIDA EXP.	-53690
	(5.66)		(2.87)		(14.99)
TEMPDIF	6.47	MIDWAY	-25429	AIR WISC.	-59057
	(0.54)		(9.55)		(7.12)
		NORTHWEST	-5502		
			(2.36)		
		NEW YORK AIR	-26327	R^2	.5571
			(8.37)		

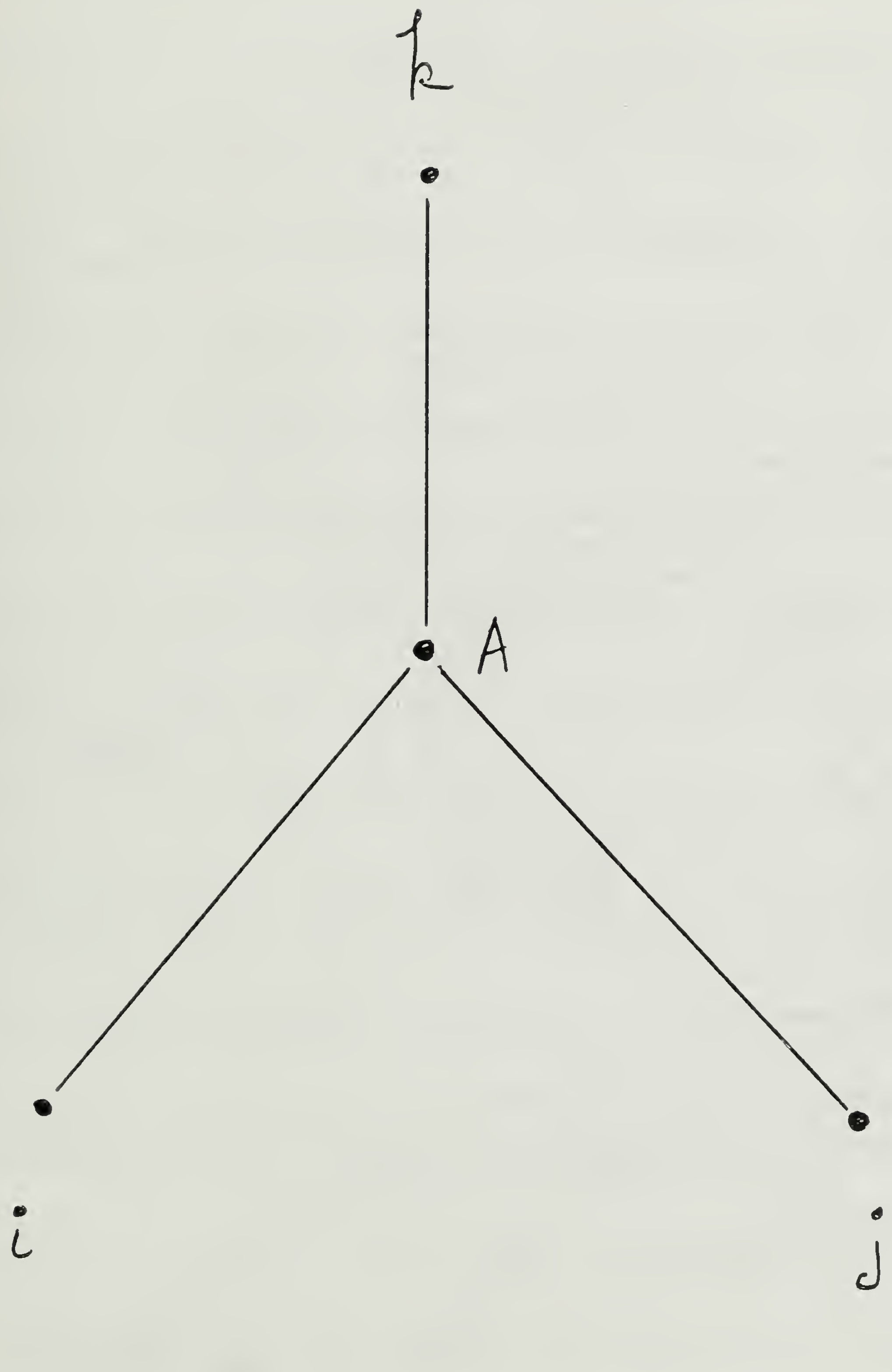
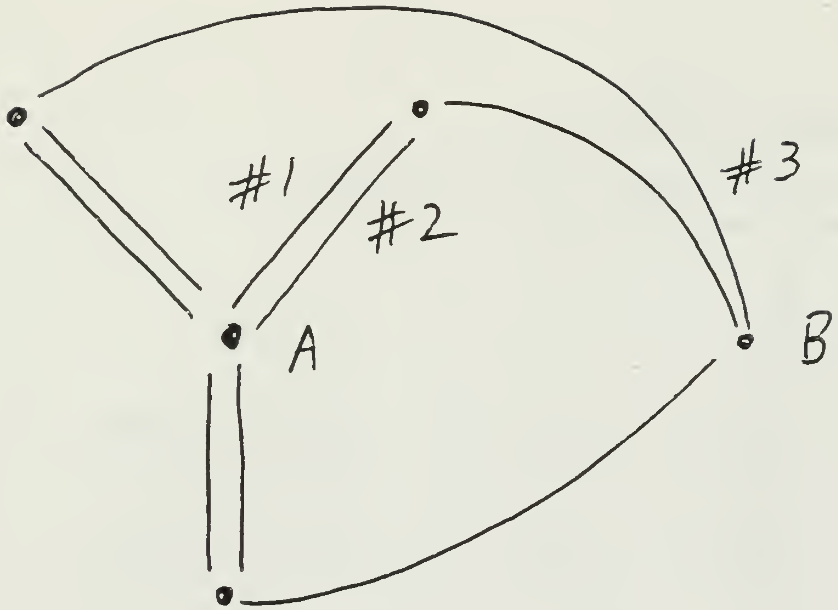
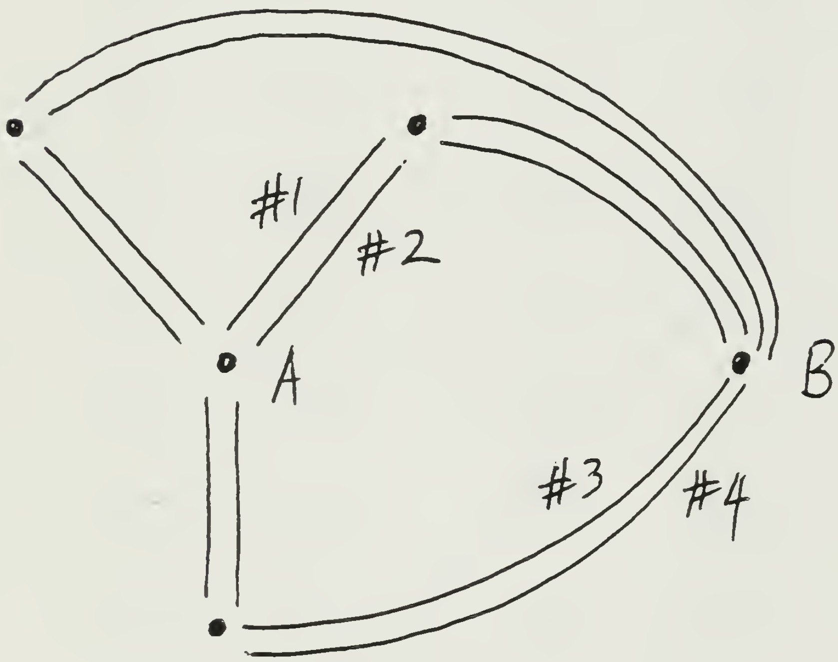


FIGURE 1.

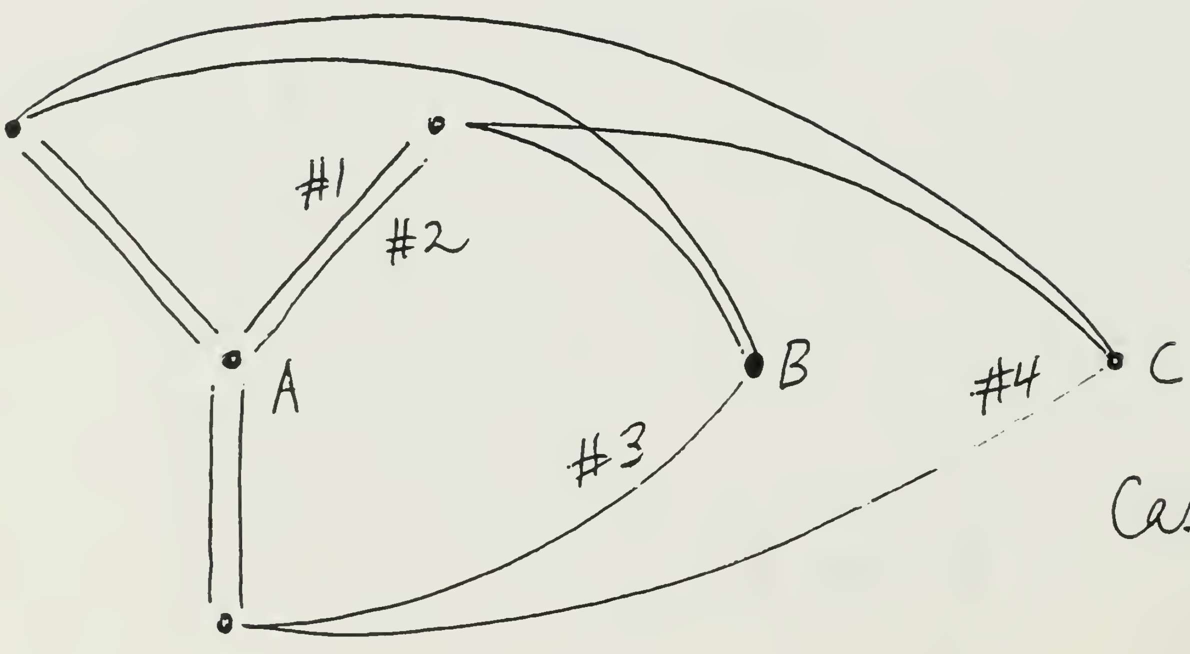
FIGURE 2.



Case I



Case II



Case III

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